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# PRODUCTION PLANNING AND SCHEDULING OPTIMISATION USING ARTIFICIAL INTELLIGENCE

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## ABSTRACT

*The paper examines the use of Artificial Intelligence (AI) approaches in optimising production planning and scheduling in manufacturing systems and limitations of conventional approaches in complexity, volatility, and real-time disruptions. Five AI algorithms i.e. Genetic Algorithms, Reinforcement Learning, Neural Networks, Ant Colony Optimisation and Deep Q-Learning were built leveraging benchmark datasets and simulated-generated data, and compared with standard scheduling strategies. The performance assessment was conducted on the major aspects such as the make span, lead time, machinery utilization, cost of operation, flexibility and capacity to absorb disruptions. The outcome indicates that the AI-based approaches are highly efficient compared to the classical scheduling and Deep Q-Learning method demonstrates the most efficient outcome, flexibility, and recovery time under a rigorous response to meeting demands but needs more training time. This balance of performance versus computational requirement made Ant Colony Optimisation and Reinforcement Learning well suited to being used in an industry setting. The results point out the potential of AI to achieve strategic advantages in process efficiency, responsiveness, and reliability, especially in dynamic manufacturing processes.*

***Keywords***: *Artificial Intelligence, Production Planning, Scheduling Optimisation, Deep Q-Learning, Ant Colony Optimisation, Manufacturing Efficiency.*

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## 1. INTRODUCTION

Production planning and scheduling are fundamental processes in operations that define efficiency, cost-effectiveness and responsiveness of manufacturing systems. These processes entail making of decisions on which products to produce, when to produce and on which resources to allocate (machinery, labour and materials). Normal means of designing schedules (This may be determined by whether the decision is a static or deterministic model in addition to the manual interventions in a schedule) are unable to deal with the complexity and volatility of contemporary manufacturing places. Globalization, mass customisation, volatile market demands, and dynamism in the supply chain has put an immense stress on the production systems to be agile, adaptive and based on data. But traditional methods even in digital forms tend to be inflexible in real-time disruptions like machine failure, supply chain failure or unexpected demand changes. This has the propensity of leading to inefficiencies and/or bottlenecks as well as longer lead times and high operation costs in such systems, hence the necessity of intelligent, scalable and responsive solutions.

Massive adoption of technologies that include the Internet of Things (IoT), cyber-physical systems, cloud computing among others that the advent of Industry 4.0 has ushered in has altered the prospect of operation optimisation. One of such technologies is Artificial Intelligence (AI) which has proven to be especially a potent tool in facilitating smart manufacturing as it contains features of pattern recognition, predictive analytics, adaptive decision-making, and real-time optimisation. Supervised learning Applications of machine learning, including neural networks, genetic algorithms, fuzzy logic, neural networks and fuzzy logic have shown good results in tackling complicated scheduling problems (holidays) by predicting demand fluctuations, balancing the allocation of resources, minimizing lead times and restructuring schedules dynamically to accommodate schedule disruptions. With such access to large-scale, multi-source data, AI systems can learn, improve, and adapt continuously and, thus, increase efficiency and resilience of supply-chain activities. The study adds to the emerging body of research on the topic of production optimisation using AI by systematically comparing the results developed using AI-powered models to the more traditional scheduling methods and analyses the potential of the explosion of advancements in this area by comparing them with the current industrial reality.

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### 1.1. Research Objectives

- To develop and implement AI-based scheduling models for production planning.
- To compare AI and traditional methods across key performance metrics.
- To assess scheduling responsiveness under high demand fluctuations.
- To evaluate resilience of methods during machine downtime.
- To identify the most effective AI algorithm for industrial use.

## 2. LITERATURE REVIEW

**Bhambri and Rani (2023)** considered AI, IoT and industrial engineering. It demonstrated real-time monitoring, automation and process optimisation in an industrial setting based on AI and IoT. To enhance the decision-making process and workflow of operations, intelligent sensors and algorithms and connectivity were employed. They found out the major disadvantages of the technology, which are high prices, cyber security risks, and the need to find qualified employees. According to the study, such inhibitions could be overcome by smart investment and upskilling. Nevertheless, convergence of AI and IoT turned factories into efficient, responsive facilities. They found out that integration will still transform manufacturing under the aspect of digitalisation and innovation. The report foresees smart, networked, self-operating industrial conditions.

**Bu et al. (2021)** created the AI Industrial Internet of Things (IIoT) structure of intelligent industrial optimisation. A middle ground advanced cooperation platform that is composed of human, machine, and information structure was suggested. This design makes production lines able to communicate and make decisions on a real-time basis. With AI-based predictive analytics, early problem detection and quality control were feasible. There was facilitation of resource access and coordination of labour using the technology, which enhanced resource usage. The authors claim that AI and IIoT made production systems more intelligent and more responsive. They demonstrated the compatibility of digital connectivity and AI to increase efficiency. The structure supported optimum throughput and motion out-of-service in the course of interconnected manufacturing terminals. One of the approaches to promote the practice of Industry 4.0 is given in the study.

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**Castañé et al. (2023)** aimed at the introduction of the AI in the chain of the main production decision-making. Machine learning and other optimisation algorithms were used to automate the process of task planning and schedule. The production was simulated by using digital twins that projected a situation throughout the project. According to figures, this modelling strength permitted manufactures to choose reasonable strategy. AI made the manufacturing lines more flexible and responsive, particularly in the case of supply chain disturbance or the change of demand. Also, the investigation aimed to enhance low environment-impact production. Real-time supervision by AI, and guidance adjustments decreased wastage of resources. The study revealed that smart manufacturing ecosystem agility, resilience, and sustainability could be enhanced with the help of AI.

**Chen et al. (2024)** surveyed AI in green logistics optimisation. They showed that AI is essential in addressing the complex issues in logistics such as route planning, vehicle scheduling and inventory. Logistical performance and minimization of environmental impact were optimised by reinforcement learning, swarm intelligence and evolutionary computing. The assessment emphasized the necessity of integrating and delivering real-time data and modification of the delivery system. AI has minimized the fuel consumption and pollution, energy-efficient logistics systems. The decision-making was aided by AI in distributed and complex supply chains, which proves their flexibility. The use of such technologies would enable the companies achieve a balance between costs, quality and sustainability. The authors revealed the conclusion that AI is critical towards greener, smarter, more agile logistics infrastructures.

**Del Gallo et al. (2023)** reviewed works with AI in scheduling the industry production. In their review, they came across the wide use of genetic algorithms, particle swarm optimisation, and neural networks in order to enhance the scheduling performance. The strategies increased schedule flexibility, resource allocation, and lead time. According to the authors, AI has been used to optimize scheduling as there are many constraints and huge amounts of data. However, in practice, notwithstanding the good theoretical and simulation outcomes, practice was also rare. Web-based industrial systems were advanced, and they experienced integration and customisation problems.

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In their study, they discovered that there was a need to conduct more research to close the gap between the theory and practice particularly in various production environments.

**Ding et al. (2023)** gave a thorough discussion of AI-capable dynamic production scheduling using rule-based as well as heuristic models to even smarter AI-based schemes. They demonstrated that machine learning and reinforcement learning supplanted memory based approaches (static techniques) and provided the ability to handle a flexible shop floor response. Researchers have claimed that AI enhanced production agility by providing dynamic rescheduling to hasten the decision-making process as well as respond to disturbances. They also focused on the history of scheduling tools, technology and how AI could be used to simulate schedules and change them in real life situations. They also demonstrated the drawbacks such as the use of a model, which is not sufficiently scalable, a requirement of the high-quality data, and the inability to decipher complex solutions generated by AI. They came to realise that there was research on building more transparent, scalable, and generalisable models following the improvement of dynamic scheduling through AI.

## 3. RESEARCH METHODOLOGY

This paper uses a quantitative, experimental, and comparative design of research to ensure the success of the Artificial Intelligence (AI) based production planning and scheduling approaches over traditional ones. The methodology design is created with a view to develop the rigorous models development, objective performance estimation, and statistical validation.

### 3.1 Data Sources

Two types of datasets were employed:

1. **Benchmark Datasets -** It was confirmed that standard Job Shop Scheduling Problem (JSSP) and flow Shop Scheduling datasets were used as much of the manufacturing optimisation research used these datasets, which were used to give common grounds to benchmark model comparisons against.

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2. **Simulation-Generated Data-** SimPy, a simulator that operates on Python was used to synthesize realistic production settings using highly strained demand and supply configurations. Such simulations were modelled to simulate job flows, machine operations, and disruption (the possibility of machine failures and priority job insertions, etc.), in a controlled environment under dynamic circumstances.

### 3.2 Sample Selection

A purposive sampling method was employed so as to include various complexities of schedules. The final sample size was 200 production scheduling instances in a wide range of manufacturing settings with different job structures, different machine configurations, and operating constraints. This was to ensure a stable testing of AI models in heterogeneous surroundings.

### 3.3 AI Techniques Implemented

AI algorithms have been chosen on the basis of their established scheduling optimisation accuracy:

- **Genetic Algorithms (GA) -** Global searching in large space problem.
- **Reinforcement Learning (RL) -** In dynamic conditions, the adaptive decision-making is reinforced.
- **Neural Networks (NN) -** To give pattern in complicated scheduling data.
- **ACO (Ant Colony Optimisation) -** For combinatorial optimisation inspired by swarm intelligence.
- **Deep Q-Learning (DQL) -** High-performance real-time decision making.

### 3.4 Tools and Software

The working and testing of AI models were done through:

- Python (NumPy, Pandas, TensorFlow, Keras, SimPy) to this to run the algorithms, to manipulate data, and to simulate it.
- MATLAB to deal with advanced modelling and optimisation routines.

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- Gurobi and CPLEX optimizers to compare optimisation benchmarks.

### 3.5 Performance Metrics

Five indicators were used to determine model performance:

1. **Make Span -** duration comprising all the jobs.
2. **Lead Time -** Duration of time taken between job release and job accomplishment.
3. **Machine Utilization-** percentage of the working time of machines available.
4. **Operational Cost -**The energy cost and delay penalties.
5. **Adaptability Score -** the capability to sustain performance during disruptions.

### 3.6 Validation and Statistical Analysis

Statistical hypothesis testing formed part of the comparative assessment in confirming the significance of the difference in performances between AI and conventional units. Multi-group comparisons made use of ANOVA and pairwise evaluations were done using independent samples t-tests. Statistical conclusion was made at the $p < 0.05$ level of significance.

## 4. RESULT AND DISCUSSION

All the three showed that in all three dimensions of performance (overall scheduling efficiency, high demands variability, and machine downtime sensitivity) AI-based solutions are much better than with conventional scheduling resulting in reduced make span, machine usage, and costs as well as increased adaptability. Deep Q-Learning has a record of excellence in efficiency, resilience and responsiveness although it needs a lot of training time. The Ant Colony Optimization and Reinforcement Learning have a good balance between training and performance requirements and thus are usable in practice. On the whole, AI-based scheduling increases operational efficiency and flexibility as well as reliability particularly in dynamic and equipment-sensitive environments.

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### 4.1 Overall Scheduling Performance

Table 1 presents a comparison between the results of different scheduling algorithms- Traditional, Genetic Algorithm, Reinforcement Learning, Neural Networks, Ant Colony Optimization, Deep Q-Learning on several important algorithms- Make Span, Lead time, Utilization of machine, Cost to run operation, Adaptability Score, and training Time. The traditional schedule has acquired the longest Make Span (320 min), the least machine utilization (65%), medium adaptability (50), and the need of no training time. In terms of AI-based approaches, Deep Q-Learning posted the smallest Make Span (230 min), the greatest machine utilization (83%), and the returns the best adaptability (90) but is the most time-consuming to train (60 hrs). Ant Colony Optimization also does exceptionally well against most of the metrics involving medium training requirements.

**Table 1:** Overall Scheduling Performance

| **Scheduling Method** | **Make Span (min)** | **Lead Time (min)** | **Machine Utilization (%)** | **Operational Cost ($)** | **Adaptability Score** | **Training Time (hrs)** |
|---|---|---|---|---|---|---|
| Traditional | 320 | 160 | 65 | 15000 | 50 | 0 |
| Genetic Algorithm | 250 | 130 | 78 | 12500 | 75 | 20 |
| Reinforcement Learning | 240 | 120 | 80 | 12000 | 85 | 50 |
| Neural Networks | 245 | 125 | 79 | 12300 | 80 | 40 |
| Ant Colony Optimization | 235 | 115 | 81 | 11800 | 88 | 30 |
| Deep Q-Learning | 230 | 110 | 83 | 11500 | 90 | 60 |

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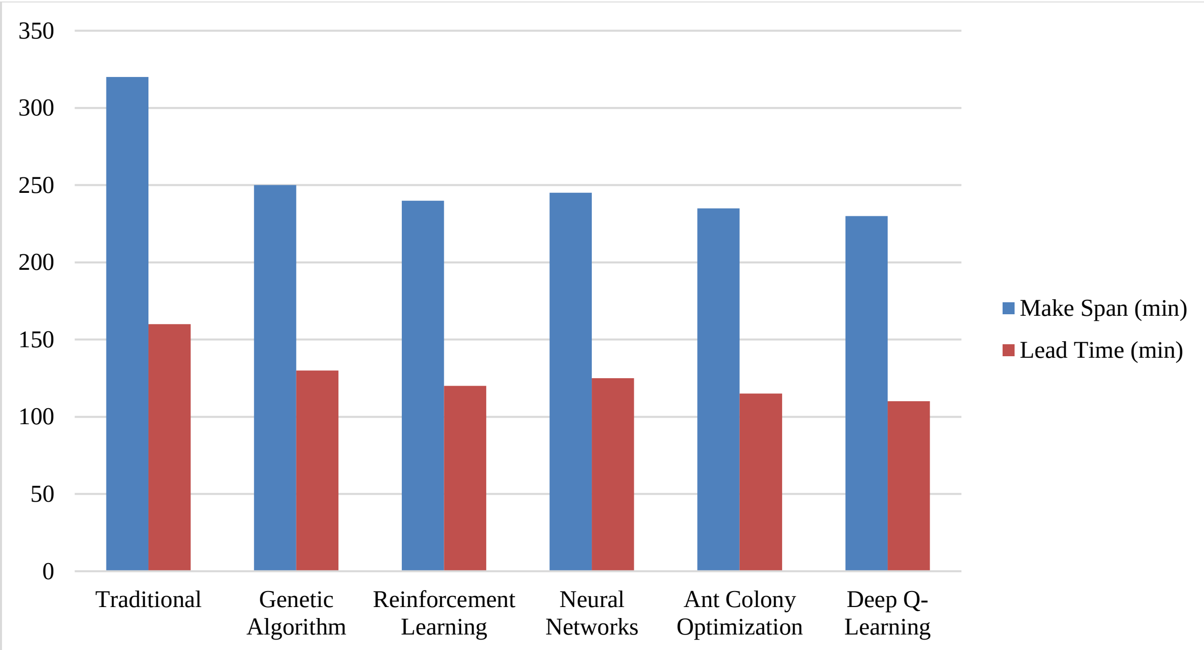


**Figure 1:** Graphical representation of Overall Scheduling Performance

The findings show that the AI-based scheduling is much more efficient, cost-saving, and flexible compared to the conventional way of doing it. Although Deep Q-Learning leads to the best operational performance, the high training time can be a limiting factor to its applications in time-sensitive environments. ACO and Reinforcement Learning are considered to be functional enough to have real-life implementation since they balance the performance and training demands. On the whole, the numbers confirm the use of AI-based optimization approaches to improve scheduling efficiency, but the application of which algorithm would depend on the acceptance of a trade-off between performance value and the expenses of the training.

### 4.2 Performance Under High Demand Fluctuation

Table 2 shows the results of various scheduling algorithms carried out under the high demand fluctuation on Schedule Success Rate (%) and Reschedule Delay (min). Traditional method has the lowest success rate (60 %) and the most reschedule delay (45 min). The Deep Q-learning algorithm is the most successful, most successful (92 percent) and has the least reschedule delay (15min) followed by the Ant Colony Optimization (90 percent, 18min) and Reinforcement

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Learning (88 percent, 20min) but both barely. The Neural Networks and Genetic Algorithms also perform close but beat them behind in both measures.

**Table 4.2:** Performance under High Demand Fluctuation

| Scheduling Method | Schedule Success Rate (%) | Reschedule Delay (min) |
|---|---|---|
| Traditional | 60 | 45 |
| Genetic Algorithm | 85 | 25 |
| Reinforcement Learning | 88 | 20 |
| Neural Networks | 87 | 22 |
| Ant Colony Optimization | 89 | 18 |
| Deep Q-Learning | 92 | 15 |

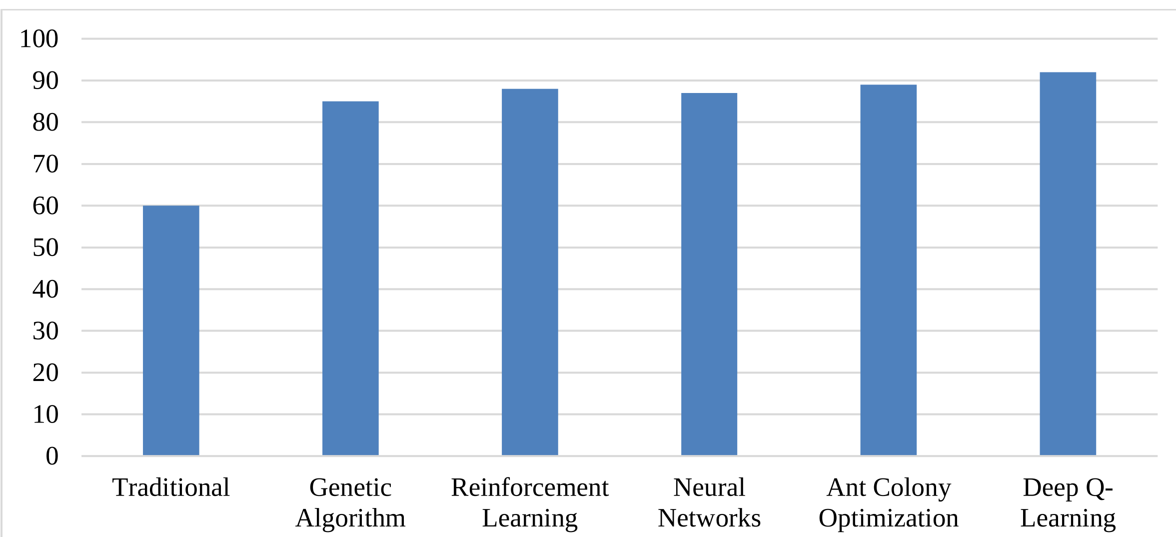


**Figure 2:** Graphical representation of Performance under High Demand Fluctuation

The findings point out that AI-based scheduling algorithms are much more effective in management of changes in demand not compared to any scheduling algorithm. Deep Q-Learning can be considered as the most resilient with close to perfect follow up on schedules and little waiting time before rescheduling which is significant to dynamic, rapidly changing production

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environments. There is also good flexibility and responsiveness in Ant Colony Optimisation and Reinforcement Learning and these methods can compete in terms of performance with only slightly greater training or computational requirements. This fact means that the AI based optimization would not only provide efficiency at the stable conditions, but also resiliency and responsiveness during unpredictable requirements by the market.

### 4.3 Sensitivity to Machine Downtime

The table 3 illustrates the sensitivity of different scheduling methods in regard to machine outage regarding Jobs Delayed (%) and Recovery Time (min). The Traditional method has the wait time of delayed jobs (40%) and the recovery time (60 min). Deep Q-Learning, on the contrary, is the best with just 14 percent jobs delayed and recovery time being 28 min. Then comes the Ant Colony Optimization with 16 percent jobs delayed and the recovery time being 30 min, whereas the Reinforcement Learning has 18 percent jobs delayed and recovery time is 35 min and Neural Networks have 19 percent and recovery time 36 min. The genetic algorithm fares better than the Traditional method yet it falls short in comparison to other methods based on AI.

**Table 4.3:** Sensitivity to Machine Downtime

| Scheduling Method | Jobs Delayed (%) | Recovery Time (min) |
|---|---|---|
| Traditional | 40 | 60 |
| Genetic Algorithm | 22 | 40 |
| Reinforcement Learning | 18 | 35 |
| Neural Networks | 19 | 36 |
| Ant Colony Optimization | 16 | 30 |
| Deep Q-Learning | 14 | 28 |

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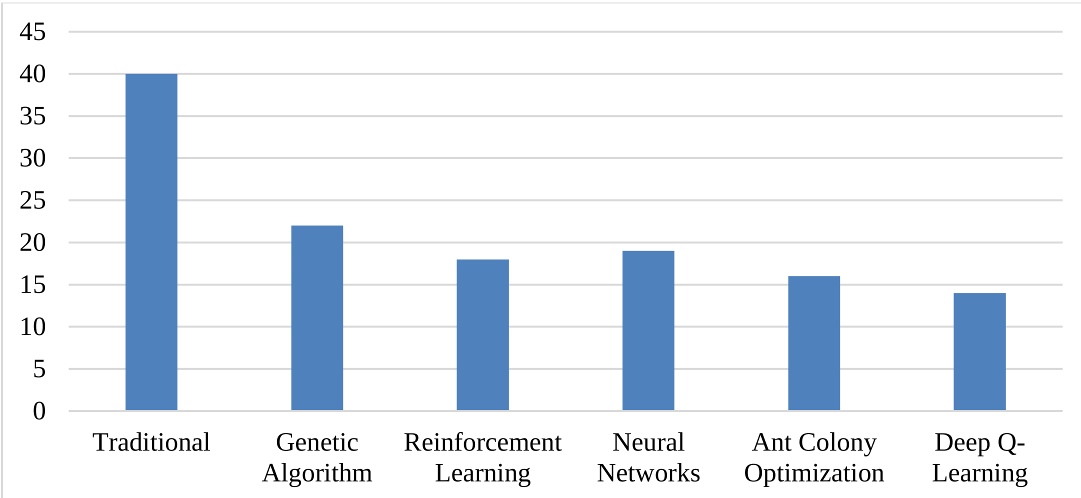


**Figure 3:** Graphical representation of Sensitivity to Machine Downtime

According to the results, AI-based scheduling enables significant improvement in machine downtime operational impact when compared to traditional methods. Deep Q-Learning has the greatest robustness, reducing both response time and the time it takes to recover, and so is best to use in applications where the reliability of the equipment is paramount. Ant Colony Optimization is very useful as well with robust downtime recovery at low delays. These findings support the flexibility and solidity of AI-based techniques that imply their tactical importance in ensuring continue operations despite unknown failures in equipment.

## 5. CONCLUSION

The comparative evaluation shows clearly that the AI-based production planning and scheduling approaches afford a much higher performance level than traditional approaches in all of the ever-assessed performance dimensions, such as efficiency, adaptability, and resilience. Of all the tested algorithms, Deep Q-Learning had the best operating performance, the lowest make span, the greatest machine utilization, the best flexibility, and the quickest recovery after disruption but at the expense of greater training requirements. Ant Colony Optimisation and Reinforcement Learning provided good, balanced results too, so could be (and were) reasonable options in an industrial setting where speed and manageable computation load are required. In the aggregate, the results validate not only the potential of AI-based optimisation in term of improving scheduling

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costs and lead times under stable conditions but as a source of robustness to decrease demand variations and incorporating maintenance and repairs of equipment, thus providing a strategic benefit in the capabilities of manufacturing cost-effective, reliable, and flexible operations.

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